as we did in our methodology to characterize the participants' living environment.

With respect to the misclassification that may be introduced due to the resolution used to classify participants, Zandbergen is correct that resampling to different resolutions did change the classification of the participants. However, the results of the analyses were consistent regardless of the resolution of the classification, indicating that while this may influence the exposure itself, it does not influence the relationship between the exposure and the outcome.

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What Can Affect AOD–$PM_{2.5}$ Association?

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Although satellite remote sensing has advanced significantly in recent years, there are inherent weaknesses in the use of this technology. The association between satellite-based aerosol optical depth (AOD_S) and air pollution monitored on the ground can be influenced by a number of factors. In their article, Paciorek and Liu (2009) highlighted the weaknesses of AOD_S to predict the spatial distribution of fine particulate matter ≤ 2.5 µm in aerodynamic diameter ($PM_{2.5}$). It is a timely article given the increasing importance of indirect methods, including satellite data, to estimate air quality because of scarce and ad hoc spatial–temporal coverage of air pollution monitored by federal regulatory methods. It is important that the robustness of these methods is evaluated, and Paciorek and Liu's article is such an attempt. However, they failed to address the role of five major factors that can influence the AOD_S–$PM_{2.5}$ association. These factors include decomposition of AOD_S by aerosol types, mismatch in spatial–temporal resolution, collocation and integration of AOD_S and $PM_{2.5}$ data, and control for spatial–temporal structure in the statistical model. Consequently, the weaknesses in Paciorek and Liu's study lead me to question their findings.

The columnar measurement of AOD_S consists of aerosols generated by anthropogenic (human) sources (AOD_{Sh}), such as emissions from industries and vehicles, and natural sources (AOD_{Sn}), such as water vapor or dust in the air. AOD_{Sn} that constitutes a large fraction of AOD_S is influenced by moving large air masses and observes a strong spatial and temporal structure. The concentration of $PM_{2.5}$, however, can vary significantly within short distances. Therefore, there is a significant mismatch in the magnitude and extent of spatial and temporal variability of AOD_{Sn} and AOD_{Sh}; without an adequate control for AOD_{Sn}, it is difficult to develop a reliable $PM_{2.5}$ predictive model using AOD_S (Kumar et al. 2008).

Paciorek and Liu (2009) recognized that the spatial–temporal resolutions of AOD_S and $PM_{2.5}$ they used were different, but they did not address how the mismatch in the spatial–temporal resolutions of these data can influence their association. The spatial resolutions of MISR (multiangle imaging spectroradiometer), MODIS (moderate resolution imaging spectroradiometer), and GEOS (geostationary operational environmental satellite) AOD were 17.6 km, 10 km, and 4 km, respectively, and $PM_{2.5}$ data were point measurements aggregated across 24 hr. A recent study suggests the strength of the AOD_S–$PM_{2.5}$ association diminishes with the increase in time interval used for their aggregation (Kumar et al. 2007). It would have been useful for Paciorek and Liu (2009) to document the implications of the spatial–temporal resolutions and aggregation of AOD and $PM_{2.5}$ (data they used) on their findings.

AOD_S retrieval and $PM_{2.5}$ are not available on the same days: AOD_S retrieval is not possible on cloudy days, and $PM_{2.5}$ data are recorded every third or sixth day. It seems that Paciorek and Liu (2009) averaged all AOD_S at 4-km pixel (i.e., 16 km^2 area; monthly and yearly) and all $PM_{2.5}$ (in the pixels where a monitoring station was situated). This could have resulted in a weak association between AOD_S and $PM_{2.5}$, because there were systematic temporal gaps in both AOD_S and $PM_{2.5}$ data sets. A reasonable approach to address this problem is to aggregate AOD_S-$PM_{2.5}$ data for those days only when both AOD_S and $PM_{2.5}$ are available.

Paciorek and Liu's method for aggregating 17.6-km and 10-km AOD_S to a 4-km pixel seems problematic. First, a radiative transfer model is used to retrieve AOD_S (Remer et al. 2006) which removes pixels with the upper 50% and lower 20% of the reflectance values. This removal can be systematic. For example, pixels with high reflectivity (such as buildings and roads) are more likely to be removed than the vegetated pixels (i.e., pixels under vegetation canopy). Thus, the centroid of a 10-km AOD_S pixel may not represent the AOD_S value for the entire 10-km area. Second, AOD_S registers a strong spatial–temporal autocorrelation. Thus, time–space kriging that utilizes large number of data points is appropriate for AOD_S aggregation rather than a single AOD_S value to avoid an area specific bias.

The robustness of AOD_S retrieval is evaluated by its comparison with the AOD recorded by sunphotometers at AERONET sites (AOD_A) (NASA 2007). The spatial resolution at which AOD_S is retrieved and the spatial–temporal intervals within which these data are aggregated may directly influence its comparison with the AOD_A . This, in turn, can influence the association between AOD_S and $PM_{2.5}$. Recent literature suggests that 1-km and 5-km AOD_S observe a significantly better association with $PM_{2.5}$ monitored on the ground than the 10-km AOD_S (Kumar et al. 2007; Li et al. 2005). Therefore, the optimal spatial resolution of AOD_S retrieval and the optimal spatial and temporal intervals for aggregating these data are critically important for developing time–space resolved estimates of air quality with the aid of AOD_S.

Because meteorologic conditions are largely influenced by the prevailing air masses and do not vary significantly within thousands of miles for a short period of time, the AOD_{Sn} component of AOD_S is likely to have a strong spatial–temporal structure. $PM_{2.5}$ that constitutes particulate mass associated with anthropogenic factors, however, varies significantly within short distances from emission sources. Therefore, to develop a $PM_{2.5}$ predictive model it is important that only AOD_{Sh} is used instead of AOD_{Sn}. If such data are not available, an alternative is to indirectly control for AOD_{Sn} and its associated spatial–temporal structure. Otherwise the predicted $PM_{2.5}$ surface is likely to have an unrealistic spatial trend, as reported by Paciorek and Liu (2009), as well as unrealistic temporal trends.

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AOD–$PM_{2.5}$ Association: Paciorek and Liu Respond

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We thank Kumar for his letter about our article (Paciorek and Liu 2009). We hope this exchange will highlight some of the key issues in using aerosol optical depth (AOD) for air quality purposes, in particular with regard to our focus on epidemiologic use. More dialogue is needed between scientists involved in remote sensing and those studying air pollution exposure and its epidemiologic effects with regard to the challenges and needs involved in making the remote sensing products helpful in applications. Our response to Kumar's letter highlights our perspective on these challenges.

We agree that in our article (Paciorek and Liu 2009) we used AOD in a relatively straightforward way, and we welcome more advanced approaches to making use of AOD; in fact, one of us (Y.L.) is heavily involved in such work. The scientific challenge is to ensure that more advanced techniques can be used over an entire continuous time period and spatial area needed in a given epidemiologic or regulatory context. In our analysis we did our best to make use of currently available AOD products and to adjust for meteorologic variables and large-scale spatial discrepancy between AOD and particulate matter ≤ 2.5 μm in aerodynamic diameter ($PM_{2.5}$) based on the data available. More sophisticated approaches will hopefully reduce the discrepancy between $PM_{2.5}$ and AOD, but this does not change the need for rigorous assessment of the use of AOD as a proxy for $PM_{2.5}$. An important test—which we explored—is the ability of AOD to help improve $PM_{2.5}$ predictions, beyond reporting correlations between AOD and $PM_{2.5}$. Furthermore, even with improved approaches in which systematic discrepancy may be alleviated, systematic discrepancy seems unlikely to disappear, and we believe serious consideration of AOD as a proxy for $PM_{2.5}$ in the future will need to consider the nature of this discrepancy and its implications for the contexts in which AOD is used as a proxy for $PM_{2.5}$.

To the extent that natural sources of AOD do not correlate with concentrations of ground-level $PM_{2.5}$, we agree with Kumar that it would be ideal to control for such sources. We used the standard MODIS (moderate resolution imaging spectroradiometer) AOD product because this product would be available to general users; however, it would be appealing if a more tailored AOD retrieval algorithm could be applied over the spatial and temporal domain of interest for a given application. From reading the article by Kumar et al. (2008; particularly p. 3390), we did not see a specific algorithm proposed to decompose AOD into anthropogenic and natural sources or to control for natural sources.

As noted by Kumar, averaging all data—rather than matching in time before averaging—reduces associations. However, when interest lies in developing a proxy for long-term average $PM_{2.5}$, the average of all monitoring data available at a regular interval should be an unbiased estimate of true $PM_{2.5}$ at the location, which is the quantity one would like to have everywhere in space. Estimated associations based on matched data therefore are an overly optimistic assessment of AOD as a proxy for true long-term $PM_{2.5}$. Of course for shorter intervals, the variability in estimates of true $PM_{2.5}$ that are based on small numbers of daily samples will contribute to reduced AOD—$PM_{2.5}$ association, so there are tradeoffs in deciding whether to match. One also needs to consider whether using matching introduces bias because missing AOD is associated with particular meteorologic conditions that also likely correlate with $PM_{2.5}$ levels (Liu et al. 2009; Paciorek et al. 2008). Finally, in unpublished work, we have seen moderate improvements in associations when matching, but these improvements were not so large as to suggest that lack of time-matching is the key reason for the results seen in our article (Paciorek and Liu 2009). The reference to results on the diminishing association with longer-term aggregation by Kumar et al. (2007) seems to reinforce our very point: One should be cautious about using AOD as a proxy for $PM_{2.5}$ when aggregating over time, but this is precisely one of the contexts in which we need proxies for $PM_{2.5}$. Health analyses do not have the luxury of only analyzing health outcomes that correspond to the time periods (and spatial locations) for which AOD is available or for which AOD is thought to be a more reliable proxy.

Given the pixel-scale AOD retrievals (and the changing MODIS pixels from day to day), to spatially align our various data sources we took the ad hoc approach of assigning to each 4-km grid cell the value of the nearest MODIS AOD pixel overlapping the grid cell, requiring the distance between the cell and pixel centroids to be no greater than the nominal distance between AOD pixel centroids. This does not fundamentally change the AOD spatial pattern but does somewhat blur the original AOD values at the pixel boundaries. We recognize that it is difficult to compare a pixel-wide AOD value to a point observation of $PM_{2.5}$, and of course one cannot expect AOD to provide information below its nominal resolution. Given this, in our statistical modeling we did our best to account for local sources of variation in $PM_{2.5}$, namely distance to roads and to point sources, that cause the point-level observations to necessarily differ from the pixel-scale AOD. One would hope that the AOD pixel value represents variation in AOD at the scale of pixels or at somewhat larger resolution (such as distinguishing variation at scales up to 50–100 km) that differentiates urban, suburban, and rural areas. We would like variation at this scale to provide information on $PM_{2.5}$ variation at the same scale that would improve prediction of $PM_{2.5}$, but our results unfortunately did not provide evidence for such improvement. It is not completely clear what Kumar is suggesting as an alternative to using the value of AOD assigned to a pixel as representative of the entire pixel area, but it seems to be an approach that uses subpixel-scale information not available in the current MODIS AOD product. This seems promising, and we welcome work on providing AOD at higher resolution and evaluating whether more highly resolved AOD improves predictions of $PM_{2.5}$. A key issue from this perspective is not the nominal resolution at which AOD is provided but the resolutions at which it is associated with spatial variations in $PM_{2.5}$.

It was not entirely clear what Kumar is suggesting in terms of how to control for natural-source AOD and its spatio-temporal structure. With regard to large-scale discrepancy between AOD and $PM_{2.5}$ that might mask smaller-scale correspondence, we used AOD and $PM_{2.5}$ data to estimate and adjust (our calibrated AOD) for large-scale spatial discrepancy that persists over time but found that this did not improve matters, suggesting that small-scale discrepancy between $PM_{2.5}$ and AOD is a major concern.

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